MODEL DEVELOPMENT FOR FORECASTING TRAFFIC MANAGEMENT OFFICE SHIPPING AND BUDGET REQUIREMENTS

THESIS

Luke E. Closson III, B.A.
Captain, USAF

AFIT/GTM/LAL/95S-3

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY
AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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THESIS

Presented to the Faculty of the Graduate School of Logistics

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Luke E. Closson III, B.A.
Captain, USAF

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Luke E. Closson III

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Abstract

This research represents an attempt to develop a quantitative tool that could be used to forecast Traffic Management Office (TMO) budget requirements for freight movements at base level within Air Combat Command. Regression analysis, using aircraft flying hours, aircraft sorties, and wing manpower levels as independent variables to predict shipping costs, was used in this research project. Each of the independent variables was aggregated and disaggregated at various levels in an attempt to develop a simple but accurate model. The results seem to suggest that aircraft flying hours, aircraft sorties, and wing manpower levels are not accurate predictors of TMO freight shipping requirements. Of the three independent variables, the most useful variable for forecasting TMO freight shipping requirements was the manpower variable, not aircraft flying hours or aircraft sorties as expected. Because of these results, the author recommends the continued use of the current naive forecasting method until a better model is developed.

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I. Introduction

Overview

Severe budget reductions have taken place inside the Department of Defense (DOD) in recent years. The end of the Cold War has served only to accelerate these reductions in military budgets. This change in fiscal policy has forced military managers at all levels to find ways to better manage available resources. The Air Force has been forced to allocate its reduced financial resources in the most economical and feasible manner. Operational units in the Air Force are continuously looking for ways to perform their jobs better, smarter, and more efficiently. One way units can manage their resources more efficiently is by accurately forecasting their requirements. If requirements are accurately forecast, senior leaders can better allocate resources to meet those forecasted needs. Accuracy in forecasting not only allows for more efficient distribution of funds during the budget formulation process, but also adds credibility to the entire budget formulation process.

Air Force Traffic Management Officers (TMO) face daily requirements to ship cargo worldwide in an effort to maintain aircraft readiness. Adequate funding must be made available to meet these mission requirements; however, budget requirements vary greatly from base to base and month to month because they are dependent on customer

requirements. These customers represent the entire wing structure including aircraft maintenance, supply and other base agencies.

To ensure adequate funding, TMOs must be provided with a tool that can accurately forecast budget requirements for future years. If the TMO is to successfully obtain the funds required, the budget request must be both realistic and defensible. One method to ensure that the budget request is defensible is to develop a quantitative tool that accurately forecasts mission requirements.

Presently, there is no tool available to TMOs to aid in forecasting shipping requirements or budget requests. Most TMOs simply use their current year's budget allocation and add some amount to account for inflation and unexpected events and hope they guess right (Helton, 1994). This method is hardly scientific and is certainly not defensible or realistic in this era of funding shortages. A tool must be provided to TMOs that will enable them to accurately project future funding requirements at base level to meet mission requirements. A failure to provide a quantitative defense to budget requests usually results in funding below what is required. If TMOs are underfunded, wings are forced to pull resources from other mission-related functions to fill shortfalls if mission-critical items are to be shipped.

Specific Problem

An accurate and reliable forecasting method to predict base level shipping requirements is essential to ensure realistic and defensible transportation budget submissions. A tool must be provided to TMOs that can be used to accurately predict their budget requirements. A failure to provide such a tool serves only to further reduce confidence in the budget formulation process.

Objectives

Two objectives will be addressed in this thesis in an effort to address this lack of a forecasting tool. The first objective is to determine if there is a relationship between flying hours, number of sorties flown, or manpower levels and dollars spent shipping cargo by TMOs. The second objective is to develop a model that will accurately forecast transportation shipping costs for future years for use in developing transportation budget requests. The end result of meeting these objectives will be a model that will provide more accurate and reliable forecasts than the "last year plus 10%" method currently employed by many TMOs Air Force wide.

Research Scope

This research will be limited to operations and maintenance (O&M) funds allocated to traffic management offices at wing level within Air Combat Command (ACC). The O&M funds represent a separate appropriation from the funds managed by Headquarters Air Force Materiel Command (HQ AFMC) known as second destination transportation (SDT) funds. This research also does not consider those funds used for the movement of household goods or passenger movements, as these funds also represent different funding appropriations (Izbicki, 1995). Although these O&M funds are used for different shipping activities than SDT funds, a close review of how HQ AFMC forecasts SDT requirements can provide significant insights into the issue of forecasting transportation requirements at base level.

II. Literature Review

Overview

Research in developing a model that accurately forecasts budget requirements for the movement of freight has primarily focused on forecasting SDT from a headquarters perspective. Though the research presented in this thesis will not directly address SDT, a discussion of how HQ AFMC forecasts SDT is relevant. This research project will focus on the forecasting of shipments paid with base O&M funds, rather than shipments paid with SDT funds. The intent of this chapter is to review previous research regarding the forecasting of SDT requirements and to review a forecasting technique used to forecast budget requirements for base level vehicle maintenance activities within ACC. A review of the AFMC's SDT forecasting methods lays a foundation for several variables and methods used to forecast freight requirements. A review of ACC's vehicle maintenance forecasting methods provides an alternative view of how to forecast budget requirements for transportation activities.

Second Destination Transportation

In order to provide a clear definition of SDT, the term first destination transportation must be clearly understood. First destination transportation (FDT) essentially represents the movement of cargo or property from the point of origin, whether a contractor or supplier, to a military storage point. Air Force Instruction 65-601, Volume I, defines first destination transportation as:

> Transportation required to effect the delivery of materiel from a procurement source (including DOD industrial activities that fabricate new material, but not if the industrial activity only reworks the item or component) outside the DOD supply system to the first point at which the Air Force takes possession or ownership. In those cases where the Air Force accepts a production item at the manufacturer's plant, or source of production, and legally owns the item,

> FDT extends to the first point of delivery for either use or storage. It includes the charges for freight, cartage, and demurrage incurred incident to shipment of the materiel. (AFI 65-601, Vol. I, 1994:222)

SDT funds are centrally managed by HQ AFMC and should not be confused with O&M funds used at base level. Air Force Instruction 65-601, Volume 1, defines SDT as:

> Any transportation other than first destination. It includes port handling charges and charges for freight, cartage, demurrage, and other charges incurred overseas incident to shipment of Air Force property. (AFI 65-601, Vol. I, 1994:223)

In his research, Stephen Strom characterized this subsequent movement and distribution of cargo and property to include the five types of transportation shown in Table 2-1.

Table 2-1. Examples of Second Destination Transportation

1. Port handling.
2. Overocean transportation.
3. Shipments to Air Logistics Centers (ALC's) or contractor depots.
4. Shipments between bases.
5. Shipments from bases to repair facilities or depots

(Strom, 1989:2-3)

Berg and Humphrey Research. This research, conducted by Major Maurice Berg and Major Lee Humphrey in 1960 represented the first documented attempts to develop a formula to forecast SDT costs for then Headquarters Air Materiel Command. At that time, Air Materiel Command consumed the majority of the SDT budget, yet did not have an accurate tool for forecasting their SDT requirements. The primary purpose of Berg and Humphrey's research was to:

> Develop a procedure for accumulating accurate and timely historical data by individual systems for movement of second destination (Project 433 funds) transportation tonnage requirements and for applying this information to future programs for budget estimates. (Berg and Humphrey, 1960:13)

In an effort to ensure they met their research goals, they established two criteria for acceptance of any solution to the defined problem. The criteria stated that any method for computing transportation tonnage requirements and any method for accumulating the data for transportation tonnage requirements must be accurate and reliable, flexible, justifiable and economical. In an effort to develop procedures for accumulating historical data, Berg and Humphrey concluded that with the use of computers, the accumulating and storing of SDT data could be accomplished while meeting their established criteria. They also concluded that historical data represented a valid base to use in forecasting future budget requirements for SDT (Berg and Humphrey, 1960:7-11).

In seeking an effective method for predicting SDT requirements, the authors employed several formulas which attempted to arrive at an estimated tonnage requirement for future programs. Based on the tonnage estimate generated, a dollar factor was applied to arrive at the dollar cost for the budget estimate. Each of their computations was based on historical data with little statistical evidence to support their conclusions. Though much of this initial research was not statistically supported, it represents the first research to suggest the use of both flying hours and manpower authorizations as variables to be considered when attempting to forecast SDT costs (Berg and Humphrey, 1960:7-11).

Foster Report. In 1977, Newton W. Foster, Directorate of Management Sciences, Deputy Chief of Staff Plans and Programs, Headquarters Air Force Logistics Command (HQ AFLC/XRS) presented a report titled "A Working Paper on Second Destination Transportation (SDT) Forecasting." This report is no longer available but is presented in research conducted by Lamb and Sarnacki, Strom, and Moore (Lamb and Sarnacki, 1978:7; Strom, 1989:29, Moore, 1990:12). In his paper, Foster lists 21

variables that are directly or indirectly related to the SDT program for the Military Airlift Command (MAC) [now known as Air Mobility Command (AMC)] and the Military Sealift Command (MSC). A reproduction of Lamb and Sarnacki's appendix showing the 21 variables is shown in Table 2-2.

Table 2-2. Variables Related to Second Destination Transportation

Variable	Data Source
Requisitions Filled	AFLC/ACM
Requisitions	AFLC/ACM
Aircraft	AFLC/ACM
Engines	AFLC/ACM
Receipts GSD*	AFLC/LORF
Gross Sales GSD	AFLC/LORF
Gross Sales SSD**	AFLC/LORF
DPEM*** - Aircraft	AFLC/LORER
DPEM - Missiles	AFLC/LORER
DPEM - Engines	AFLC/LORER
DPEM - Other Major End Items	AFLC/LORER
DPEM - Exchangeables	AFLC/LORER
DPEM - Area Base Maintenance	AFLC/LORER
DPEM - Total	AFLC/LORER
Overseas Flying Hours	G022B System
Worldwide Flying Hours	G033B System
Receipts Off Base - Line Items	LOG-XR(Q) 7507
Receipts Off Base - Tons	LOG-XR(Q) 7507
Issues Off Base - Line Items	LOG-XR(Q) 7507
Issues Off Base - Tons	LOG-XR(Q) 7507
Manpower	USAF/PMR

*GSD: General Support Division
**SSD: System Support Division
***DPEM: Depot Purchased Equipment Maintenance

(Lamb and Sarnacki, 1978:43)

Lamb and Sarnacki Research. In 1978, Captains Christopher Lamb and Joseph Sarnacki furthered the research in the field of SDT by attempting to "develop a

method for computing tonnage estimates to derive future SDT budget forecasts" (Lamb and Sarnacki, 1978:1). Their efforts concentrated on identifying variables that could be used to accurately forecast SDT requirements and subsequently develop a computer program for forecasting the tonnage estimates.

In their study, Lamb and Sarnacki decided that 19 of the 21 variables listed in Table 2-2 were neither applicable nor feasible to use in developing their model due to the time constraints of their research project, the lack of a historical database for those variables, and the lack of future projections of those variables. Thus, their research considered two variables, flying hours and manpower, as the independent variables for predicting SDT tonnage estimates and budget requirements. Two key considerations in their use of these two variables was the availability of historical databases and the availability of future projections of each. The authors also chose to limit the scope of their research to just MAC (Lamb and Sarnacki, 1978:8-9).

The authors applied discontinuous linear regression to their data, which captured both planned and actual quarterly flying hour data and planned and actual quarterly manpower data for the fiscal years' 1973-1978 and 1974-1977 respectively. The authors chose to apply discontinuous linear regression because after plotting the data they noticed that although a linear relationship between the variables appeared to exist, there was a gap in both the manpower and flying hour variables when plotted against SDT tonnage (Lamb and Sarnacki, 1978:15).

Using this data, they developed a model with an R^2 of 0.886, which was greater than their established criteria of 0.80. The R^2 led Lamb and Sarnacki to the conclusion that their model was indeed reliable. They also determined that the discontinuous linear regression model that they developed was statistically more accurate than the delta factor method, being used by HQ AFLC (Lamb and Sarnacki, 1978:32).

The authors' objective of creating an accurate and validated model for predicting SDT requirements was accomplished, as well as the goal of developing a computerized model to compute the SDT requirements (Lamb and Sarnacki, 1978:39-40). Though this research was limited to analyzing data for MAC and cannot be generalized for the entire Air Force, it does validate the concept that projected flying hours and projected manpower levels might be useful in forecasting transportation requirements.

Strom Research. In 1989, Captain Stephen L. Strom conducted further research to model SDT funding for HQ AFLC. Some of his study stems from the regression model created by Lamb and Sarnacki in 1978.

At the time of his research, HQ AFLC was using a simple linear regression model that utilized the 40 most recent quarters of historical data consisting of both flying hours and second destination tonnage shipped. The forecasting requirements were divided into five different means of transport: MAC, MSC, Military Traffic Management Command (MTMC), which includes port handling operations, logistics airlift (LOGAIR) and Government Bills of Lading (GBL), to include commercial air and surface transportation (Strom, 1989:4-5).

Strom identified two research objectives. The first objective was to validate the current forecasting method utilized by HQ AFLC/DSXR in computing tonnage estimates to develop their future SDT budget requests. His second objective, assuming that the model was found to be invalid, was to develop a new forecasting model using the same input data that would produce more accurate and reliable tonnage estimates (Strom, 1989:10).

Regarding research objective number one, Strom concluded that the data he received did not lend itself to the use of linear regression. The data analyzed represented SDT tonnage shipments by MAC and MSC to United States Air Forces in Europe (USAFE) and Pacific Air Force (PACAF). The analysis of the data produced four distinct

data sets. By graphically analyzing the four data sets he found that SDT tonnage, when plotted against flying hours appeared to be curvilinear, cone-shaped, or blocked, depending on the data set used. In attempting to validate the model, Strom determined that at a 95 percent confidence level the flying hour parameter used to predict SDT tonnage for MSC was unstable. In testing the model, Strom computed the flying hour parameter, β_1, for each iteration of the model used by HQ AFLC. Two of the four data sets tested resulted in a rejection of the null hypothesis. These results led to a conclusion that the linear regression model being used by HQ AFLC was invalid and therefore was an inappropriate method for forecasting second destination tonnage requirements (Strom, 1989:62).

The second objective was approached by developing a Box-Jenkins time series forecasting model for each of the four data sets. Strom chose the Box-Jenkins technique because it allows for the identification of patterns in time series data sets and uses those patterns to build an appropriate model (Strom, 1989:63). The results from this second analysis, however, proved to be inconclusive. The Box-Jenkins models for two of the SDT time series data sets were found to be no more accurate than the models presently used by HQ AFLC. The Box-Jenkins models developed for the other two SDT time series data sets were validated at a 95 percent confidence level, though they proved to be marginally less accurate than the current models used by HQ AFLC which were found to be invalid during the course of Strom's research (Strom, 1989:85-86).

Strom further noted that although the data used in the 1970's produced a linear relationship, the relationship had since changed and was no longer linear, therefore the model must also change. Strom acknowledged that although he was unable to produce an accurate and statistically valid model, the need for one still existed and was a topic for continued research. Finally, Strom suggested that the data set used to forecast SDT requirements should be increased from 40 quarters of data to at least 50 or 60 quarters of

data, possibly disaggregating the data sets to monthly data. He further stated that flying hours should not be the only independent variable considered and suggested manpower and weapon system type as possible independent variables (Strom, 1989:85-87).

Moore Research. In 1990, Moore introduced the use of multiple regression and neural network models to develop SDT requirement's forecasts. At the time of his research, HQ AFLC/DSXR was still using a simple regression equation to forecast SDT requirements using historical quarterly flying hours as an independent variable. The forecasts were developed for the next six quarters using an iterative approach using the 40 most recent quarters of data (Moore, 1990:5-7).

Moore's research represented the first attempt to develop a forecasting model using flying hours by aircraft type and manpower levels. In his research, Moore established two objectives:

> 1. Develop multiple regression and neural network models using flying hours by aircraft type and military population variables that were statistically more accurate than the DSXR simple regression models.
>
> 2. Determine whether the neural network or the multiple regression models were more accurate forecasting models. (Moore, 1990:9)

Moore's research was limited to studying data collected from overseas locations in PACAF and USAFE and SDT tonnage data collected from MAC and MSC (Moore, 1990:10).

As mentioned earlier, Moore's research represented the first attempt to introduce a flying hours broken down by aircraft type into an equation for forecasting SDT requirements. In addition, Moore also introduced a variable that reflected military population data for the areas being analyzed (Moore, 1990:49).

In his initial analysis, Moore used Gardner's trend and seasonal analysis and Gardner's business cycle pressure analysis methodology. Moore then created a multiple regression model using both flying hours by aircraft and military population levels. This

regression model was determined to be valid with a 95 percent level of confidence (Moore, 1990:49-55).

In developing the neural network models, Moore used one technique based on developing the network model with data representing independent variables and the dependent variables similar to the multiple regression models. He also applied a second technique that involved time series development. Each of these models was evaluated for its ability to recognize patterns and its ability to accurately forecast SDT requirements (Moore, 1990:57-60).

Moore's results led him to the conclusion that for each of the data sets analyzed, both the multivariable neural network models and the multiple regression model proved to be more statistically accurate and more reliable than the simple regression model being used by HQ AFLC/DSXR at that time. When comparing the multivariable neural networks with the multiple regression model, both models achieved relatively comparable forecasting accuracy. Moore also concluded that the addition of flying hours by aircraft type and military population as independent variables significantly contributed to improving forecasting accuracy of the models (Moore, 1990:150-156).

Vehicle Maintenance Funding

Research in the forecasting of budget requirements has not been limited to second destination transportation. There have also been research efforts to develop models for forecasting budget requirements for vehicle maintenance activities. In April 1992, the Headquarters Air Combat Command Directors of Finance (HQ ACC/FMA) and Transportation (HQ ACC/LGT) sponsored an initiative to restructure the transportation vehicle maintenance budgeting process. Several transportation squadrons were not able to effectively develop budget requests nor defend their budget submissions and as a result saw reduced budgets. This review indicated that squadrons across the command may

have been funded at different levels because every squadron used a different method to develop its annual budget requests. The primary goal of HQ ACC/LGT's in this restructuring of the budget process was to ensure that funding was distributed consistently and equitably among all vehicle maintenance flights in ACC (HQ ACC/LGT, 15 April 1992:1-2).

When analyzing the data, HQ ACC/LGT attempted to find a correlation between dollars spent maintaining vehicles and the number of vehicles assigned to a wing. Using three months of data, October 1991 to February 1992, HQ ACC/LGT found a correlation between previous vehicle maintenance expenditures and the number of vehicles assigned. Based on their analysis, HQ ACC/LGT established a cost per equivalent baseline for the command of $30.00 per vehicle equivalent. Vehicle equivalents essentially represent a standard measure for vehicles and are typically related to maintenance labor hours (AFM 77-310, Vol. II, 1991:113). Simply stated, vehicle equivalents are assigned based on the maintenance level required for a specific vehicle type. A standard six passenger sedan is relatively simple to maintain, therefore it is listed as one vehicle equivalent. A truck/tractor wrecker, on the other hand, represents a much more complex system and requires greater effort to maintain, therefore it is listed as four vehicle equivalents. An example of some vehicles and their assigned vehicle equivalents is provided in Table 2-3. By summing all of the vehicle equivalents assigned to a wing, the total number of vehicle equivalents is obtained.

Table 2-3. Excerpt of Vehicle Equivalent Listing

Type Vehicle	Vehicle Equivalents
Sedan, Regular, 6 Passenger	1.0
Sedan, Compact, Law Enforcement	2.0
Bus, School, 19-20 Passenger 4 x 2	2.5
Ambulance, Modular 4 x 2	1.5
Mini-Van, 4 x 2	1.5
Semitrailer, 50 Ton, 6 Wheels	0.4
Truck, Tractor, Wrecker, 6 x 6 5100# GVW	4.0

(AFM 77-310, Vol. II, 1991:113-114)

Though the time frame used to establish the correlation is too small for statistical analysis, cost per equivalent budgeting has proven effective in providing adequate funding to base vehicle maintenance activities. The command baseline of $30.00 per vehicle equivalent represents the average costs for transportation squadrons in ACC to maintain one vehicle equivalent for one month. In developing the $30.00 per equivalent baseline, the command staff also developed allowances for vehicle maintenance activities to apply for variances, to be added to the command baseline, for bases encountering unique circumstances. A list of some of these variances is shown in Table 2-4.

Simply stated, the budget request is formulated by each base vehicle maintenance officer by multiplying the number of vehicle equivalents assigned to a wing times the command determined baseline times twelve months and adding any HQ ACC/LGT approved variances. This standard budgeting system was dubbed cost per equivalent budgeting. This method of allocating funds to base vehicle maintenance activities achieved its goals by providing funding that was distributed consistently and equitably among all vehicle maintenance flights in ACC (HQ ACC/LGT, 16 June 1992:2-3). In the

same manner as vehicle maintenance activities, it is essential that all managers, including traffic managers at base level, be provided with a tool which can assist them in forecasting their budget requirements. If a tool can be provided to the traffic manager to accurately forecast transportation requirements, funds can be consistently and adequately distributed to traffic managers throughout ACC. Presently, however, a tool does not exist for the traffic manager to use to accurately forecast traffic management requirements.

Table 2-4. Variances Affecting Vehicle Maintenance Funding

Factor	Effect on Funding
1. Annual base supply cost inflation rate	As the cost inflation rate increases, funding increases proportionally
2. Age of vehicle fleet	Older vehicles require more maintenance; thus more funding
3. Utilization rates	Bases with higher vehicle utilization rates require higher funding levels
4. COPARS cost differential *	Different funding required at different bases depending on COPARS contract
5. Cold weather climate	Northern bases have added requirement for snow removal equipment and have significant summer rebuild programs
6. Corrosion rating	Bases near high corrosion areas have a higher need for funding for corrosion prevention
7. TDY support	Some command bases host major exercises and require more funding for additional vehicle support
8. Emission laws	Bases located in states with high emissions standards such as California and Arizona require additional funding
* COPARS - Contractor Operated Parts Store	

(HQ ACC/LGT, 16 June 1992:2-3)

Summary

There has been a good deal of research in the area of forecasting SDT requirements for HQ AFLC. While there has been little research conducted to evaluate the formulation of budgets for base level shipping activities, lessons can be learned from SDT research and HQ ACC/LGT implementation of cost per vehicle equivalent budgeting. By applying some of the drivers identified in forecasting SDT requirements such as analyzing flying hours by aircraft type and manpower levels, an accurate model for forecasting requirements at the base level can be developed.

The traffic management community can benefit from both research streams. This research project will attempt to find a relationship between traffic management shipping activities and flying hours, sorties flown, and manpower assigned to wings within ACC. Success in identifying a relatively strong relationship could solve the same problem that HQ ACC/LGT solved with the implementation of cost per equivalent budgeting for vehicle maintenance. The effects of applying such a technique to traffic management office budgets could allow for the computation of a budget that is distributed both consistently and equitably and a budget that can be easily and accurately forecasted.

III. Methodology

Overview

This chapter seeks to provide a review of various forecasting methodologies available and to provide a justification for the methodology selected for this research project. Since the primary goal of this research was to develop a reliable and valid model for forecasting transportation shipping costs, a review of various forecasting models will be accomplished. A discussion of the variables considered for the model and how the data were collected will follow. The chapter will conclude with a discussion of the type of forecasting method used and how the data were to be handled.

Forecasting Models

Forecasting model choice should be based upon several decision criteria including degree of accuracy required, forecasting time horizon, costs involved in producing the forecast, degree of complexity, and availability of data. Often the most important criteria is accuracy. Forecasting models typically are categorized within two broad categories as either qualitative or quantitative. The purpose of this research is to identify a statistically valid and reliable model for forecasting transportation freight requirements; therefore, only quantitative forecasting models will be considered. Quantitative forecasting models can further be grouped into two broad categories: time series models and causal models (Abraham and Ledolter, 1983:4-7).

Time Series Analysis. The primary function of time series analysis is to identify trends over time and to build a model based on those patterns found. Time series methodologies for forecasting "are based on the notion of assigning weights to recent observations of the item to be forecast (e.g., sales or shipments) and then using the weighted sum of those observed (actual) values as the forecast" (Wheelwright and

Makridakis, 1980:37). Time series analysis encompasses several techniques including naive methods, moving average, exponential smoothing, and autoregressive/moving average (ARMA) technique. Each of these will be briefly discussed in terms of how to apply them and the advantages and disadvantages associated with each methodology.

Naive Approach. The naive approach to forecasting is one of the simplest time series forecasting methods. This method simply uses the most recently observed value as the basis for its forecast (Wheelwright and Makridakis, 1980:37-38). By forecasting budgets using "last year plus 10%," most TMOs within ACC are using this type of forecasting model by default. It is possible that the use of a more sophisticated model may not provide sufficient improvement in accuracy over a naive approach. This type of model is typically used for relatively short time horizons.

Moving Average. A moving average is often applied when the forecasting horizon is relatively short and randomness is of great concern. The primary advantage associated with the moving average is in its ability to reduce the effects of randomness. Applying this method consists of "weighting N of the recently observed values by 1/N." As new observations are added to the equation, older observations are discarded (Wheelwright and Makridakis, 1980:37-38). Typically, the moving average technique is not applied for relatively long forecasting time horizons.

Exponential Smoothing. Exponential smoothing is very similar to the moving average technique. The primary difference between exponential smoothing and the moving average is that the exponential smoothing technique does not apply a constant weight for the N most recent observations. An exponential decreasing set of weights is applied in order to place more weight on the most recent observations. The effects of this technique are that the most recent data are given greater importance. As with the moving average, however, it is usually applied when the forecasting horizon is relatively short (Wheelwright and Makridakis, 1980:38).

Autoregressive/Moving Average (ARMA). This type of model is basically an extension of the moving average and the exponential models and represents the most sophisticated of the time series forecasting models. The most commonly used method of ARMA is the Box and Jenkins methodology. This model essentially determines the optimal number of observations to include in the model and identifies the weights for each observation included in the model. An advantage of this type of methodology is that the Box and Jenkins model also provides valuable statistics about the forecast as well as an expected value for the forecast (Wheelwright and Makridakis, 1980:38-39).

Causal Methodologies. Causal models represent the second type of quantitative forecasting tool and includes such models as regression and econometrics. As with the discussion of time series analysis, a brief discussion of each of these methodologies will be accomplished.

Regression. Regression analysis is a statistical technique that is primarily concerned with the identification of relationships between two or more variables. When more than two variables are considered it is referred to as multiple regression. Regression analysis considers the previous observations and estimates the relationship between each of these variables. Based on these relationships, accurate forecasts can be made. One significant advantage of regression analysis lies in its ability to provide powerful evidence for a causal relationship between several variables and the variable being forecast. Regression models, both simple regression and multiple regression, are extensively used for relatively longer forecasting horizons (Wheelwright and Makridakis, 1980:39).

Econometrics. The econometric model is an extension of the regression model in that econometric model uses two or more regression equations simultaneously. One of the inherent advantages of an econometric model is that it can capture an interrelationship among the independent variables in any single equation by including the interrelationship in another equation and determining their values simultaneously. Though

this type of model provides an excellent representation of the real world, this model is often extremely complex and cost prohibitive. This type of model is most appropriate for highly aggregated data and for long range projections (Wheelwright and Makridakis, 1980:40).

Model Selection

When attempting to determine which type of model to select, the first step is to determine whether time series analysis or a causal model is most appropriate. An advantage associated with the causal model is its ability to identify key relationships and their relative strengths. For this research project, the regression model, despite its cost and difficulty in developing, was chosen over the time series analysis alternatives because of its ability to serve as both a predictive and an explanatory model. Another advantage to selecting a regression model was in its relative ease in modifying the model to include new variables, which would aid further research in this area.

One of the goals of this research project was to identify variables which could accurately forecast transportation shipping requirements. Regression analysis provided a strong argument for causality and helped identify not only whether an independent variable was positively or negatively related to the dependent variable, but also identified the relative strength of those relationships found. The use of time series analysis such as exponential smoothing or moving averages could identify trends and make forecasts but they would not indicate what caused any changes in the forecasts or why. Regression analysis would indicate what caused changes in the forecasts and would be explanatory in nature. None of these goals could be achieved with a standard time series analysis.

Variable Selection

Three independent variables were selected to serve as predictor variables for the dependent variable, base level transportation shipping requirements in dollars (TSR). The

three independent variables selected included aircraft flying hours (AFH) (disaggregated by weapon system and base), aircraft sorties (AS) (disaggregated by weapon system and base), and manpower levels (ML) (disaggregated by base). The use of these variables was based on the premise that aircraft flying hours allocated to each wing, aircraft sorties flown by each wing, and base manpower levels could be used to forecast budget requirements for each base's shipping requirements. The selection of these variables was consistent with those used by Moore and Strom in their research to forecast SDT budgets (Strom, 1989:85-87; Moore, 1990:150-156).

The selection of AFH as an independent variable was made based on consultations with the ACC transportation staff, previous SDT forecasting research conducted by Moore and Strom. Previous research into forecasting SDT found that the use of AFH as an independent variable increased both the reliability and validity of the forecasting model (Strom, 1989:85-87; Moore, 1990:150-156; Izbicki, 1995). The AFH variable was also selected because it was thought that the number of aircraft parts shipped was a function of the number of hours an aircraft was flown; the assumption being that the more hours the aircraft was flown, the more frequently it would require repair. This change in frequency of repair would reasonably have a direct impact on the number of parts shipped and therefore an impact on shipping costs. Since much of the shipping requirements at each base were a function of shipping aircraft parts, it was deemed logical to assume that a change in AFH might result in a change in shipping requirements and therefore shipping costs. Since AFH were forecasted by base and weapon system approximately six months prior to each fiscal year the data would be available to be used in a forecasting model. Forecasted flying hours also tended to equal the actual hours flown by each wing, as such AFH could serve as a stable independent variable for forecasting TSR.

The variable AS was chosen as an independent variable for many of the same reasons as the AFH variable. Again, since much of the shipping requirements at each base

was a function of shipping aircraft parts, it was logical to assume that a change in AS might result in a change in the number of parts shipped and thus a change in shipping requirements and ultimately shipping costs. Since the number of flying hours flown and the number of aircraft sorties flown most likely would be highly correlated, both would not be included in a single forecasting model. The goal was to choose variables that were highly correlated with shipping requirements, but not highly correlated with each other. The use of AS to forecast shipping requirements might not have proven possible for several types of weapon systems. From the data received from the flying hour office at HQ ACC, AS were projected only for fighter type aircraft. Though this variable might not have been usable for other types of weapon systems it was nevertheless considered for bases with fighter type aircraft.

The use of ML as an independent variable was based upon both the recommendations and conclusions of previous research in forecasting SDT(Strom, 1989:85-87; Moore, 1990:150-156). It was also thought that using ML as an independent variable would contribute to a more robust model that could possibly be used to forecast future transportation shipping requirements for bases which possess no aircraft. One could surmise that a larger base populace may result in greater TSR for that base.

In developing a forecasting model for predicting TSR an effort was made to consider as many variables as possible which might have served to accurately forecast base level TSR for the next year. It was thought that the use of programmed flying hours, estimated aircraft sorties, and programmed manpower levels for each wing in ACC might serve as accurate predictor variables to forecast base level TSR for the following year.

Data Collection

The first step towards developing a model which provides an accurate forecast of future transportation costs is to collect accurate data. The primary data collected represented historical fiscal year (FY) data provided from the HQ ACC Financial Management Office (HQ ACC/FMA), the HQ ACC Manpower Office (HQ ACC/XMMPD) and the HQ ACC Flying Hours Program (HQ ACC/DOSBB.) The merger of parts of the Strategic Air Command (SAC) and the Tactical Air Command (TAC) into the Air Combat Command in June of 1992 made the collection of data difficult. Most of the data, as it existed in TAC, were still available; however, much of the data as it existed in SAC were not available. Since the formation of ACC, all ACC data were relatively simple to obtain.

Finance Data. The data collected from the finance office represented actual historical O&M dollars spent by ACC wings at their cargo shipping activities for FY90-FY95. Five years of data were collected because HQ ACC/FMA only maintained the data, disaggregated by base and weapon system, for five years. For fiscal years FY90-91, the only data available for analysis were data representing what was then known as TAC. The SAC data, representing primarily bomber and missile wings, were not available. Comprehensive financial data for FY92-94 were available for analysis. The ability to obtain only five years of financial data proved to be a limiting factor in this research.

The data obtained from HQ ACC/FMA were sorted by the fiscal year the dollars were spent, the wing where the dollars were spent and the category in which dollars were spent in the traffic management activity. Only those funds actually used to ship or to support the shipment of cargo and allocated by the traffic management activity, specifically responsibility center/cost center (RC/CC) codes XX4220, were considered for the model. The specific element of expense investment codes (EEIC) considered and the description of each EEIC are shown in Table 3-1.

Table 3-1. EEICs Collected

EEIC	Title Description
462XX	Transportation of Property Via Commercial Air
463XX	Transportation of Property Via Commercial Surface Mode
469XX	Miscellaneous Charges for Transportation of Property
609 *	General Support Supplies and Materiel
* 609 funds included to consider costs to procure supplies necessary to construct shipping containers	

<u>Aircraft Flying Hours Data</u>. The data collected from the flying hours office includes total number of hours flown by ACC wings sorted by major weapon system and by wing for FY90-95. Again, as with the finance data, SAC flying hours data for FY90-92 were unavailable. TAC flying hour data from FY90-92 were collected as well as all ACC flying hour data for FY93-94. The data from the flying hours office included both projected and actual flying hours for each wing and both the projected and the actual number of aircraft sorties flown by each wing sorted by wing and major weapon systems. The projected values for both AFH and AS are suspect for FY90-93 because the projected AFH and projected AS values for FY90-93 were "pencil whipped" to show actual aircraft sorties flown and actual hours flown. Because of this, the accuracy of these projected values could not be determined. Values for FY94 did, however, represent real projections. Historically, however the programmed flying hours tended to closely represent the actual hours flown by each wing, so the AFH variable was considered to be accurate for forecasting.

<u>Manpower Data</u>. The data collected from the manpower office included total number of personnel assigned to ACC wings for FY90-94 and projected number of manpower authorizations for ACC wings for FY95. These data were further disaggregated by officer, enlisted, and civilian workforce assigned to each wing within

ACC. This data, contrary to the finance and flying hour data, did not suffer from the same problems of missing data for SAC and TAC. The data for ML for FY90-94, for SAC, TAC, and ACC were easily obtained.

Data Analysis

The data collected were input at the most disaggregated level possible. Each data line represented one base for a specific year along with the specific number of hours and sorties programmed and flown for that year by aircraft type. The AFH and AS data were input in such a way as to allow for aggregation of certain types of aircraft. Thus, all fighter type aircraft could be aggregated to determine if a forecasting model for only fighters could be accurately developed rather than developing a model for each specific airframe. Each data entry also included the programmed ML, disaggregated by officer, enlisted and civilian, and included the actual dollar amounts spent shipping cargo during the fiscal year for each base measured. The data was input into spreadsheet format to allow for ease of entry and to allow for exporting to a data file usable by the statistical analysis computer program SAS.

Variable Aggregation. As mentioned earlier, the data were entered in such a way as to allow for aggregation of the data. Once the data file for SAS had been created, like aircraft types were combined to create new variables to be included in new regression equations. The new variables created, for AS and AFH, included fighters (FTR), bombers (BMR), tankers (TNK), cargo (CGO), transport (TSP), helicopter (HEL), and other (OTH). The specific variables consisted of the aircraft shown in Table 3-2.

Table 3-2. Aggregated Category Variables

FTR	BMR	TNK	CGO	TSP	HEL	OTH
A-10	B-1	KC-10	C-130	C-21	HH-3	E-3
EF-111	B-2	KC-135	C-135	C-27	HH-60	E-4
F-111	B-52			CT-43	UH-1	E-9
F-117						EC-130
F-15						HC-130
F-15E						OC-135
F-16						RC-135
F-4						TC-135
OV-10						WC-135
T-37						
T-38						

These seven variables were then further aggregated together into a single variable, all aircraft flying hours (AAFH) and all aircraft sorties (AAS), to determine if a reliable model could be built using the minimum number of independent variables.

Aircraft Flying Hours Models. A regression model using AFH disaggregated by aircraft was the first model developed with TSP as the dependent variable and each aircraft type's flying hours as the independent variables. This would result in 34 independent variables. This model is shown as:

$$TSR = \beta_0 + \beta_1 AFH_1 + \beta_2 AFH_x + \beta_3 AFH_x + \ldots + \beta_{34} AFH_{34} + \varepsilon \qquad (1)$$

where: TSR = Transportation Shipping Requirements in dollars

AFH_1 through AFH_{34} = AFH by type of aircraft

A second regression model was also developed that differed from the initial AFH model, in that the independent variables were AFH aggregated by category as shown in Table 3-2. This model would result in seven independent variables. This model is shown as:

$$TSR = \beta_0 + \beta_1 FTR + \beta_2 BMR + \beta_3 TNK + \beta_4 CGO + \beta_5 TSP + \beta_6 HEL + \beta_7 OTH + \varepsilon \quad (2)$$

where: TSR = Transportation Shipping Requirements in dollars

FTR = Fighter Flying Hours

BMR = Bomber Flying Hours

TNK = Tanker Flying Hours

CGO = Cargo Flying Hours

TSP = Transport Flying Hours

HEL = Helicopter Flying Hours

OTH = Other Flying Hours

The final AFH model was constructed similar to the previous two models except only a single independent variable, AAFH, was used to forecast the dependent variable, TSR. This model is shown as:

$$TSR = \beta_0 + \beta_1 AAFH + \varepsilon \quad (3)$$

where: TSR = Transportation Shipping Requirements in dollars

AAFH = All Aircraft Flying Hours

<u>Aircraft Sorties Models</u>. Three regression models using AS disaggregated by aircraft was also developed in a similar manner as the regression models for AFH was developed. The first model developed used AS disaggregated by aircraft type as the

independent variable and TMO budget as the dependent variable. This model would, as with the disaggregated AFH model, resulted in 34 independent variables and is represented by the equation:

$$TSR = \beta_0 + \beta_1 AS_1 + \beta_2 AS_x + \beta_3 AS_x + \ldots + \beta_{34} AS_{34} + \varepsilon \quad (4)$$

where: TSR = Transportation Shipping Requirements in dollars

AS_1 through AS_{34} = AS by type of aircraft

A second regression model was also developed, again using TSR as the dependent variable. This model differed from the initial AS model, in that the independent variables were AS aggregated by category as shown Table 3-2. This model resulted in seven independent variables and is represented by the equation:

$$TSR = \beta_0 + \beta_1 FTR + \beta_2 BMR + \beta_3 TNK + \beta_4 CGO + \beta_5 TSP + \beta_6 HEL + \beta_7 OTH + \varepsilon \quad (5)$$

where: TSR = Transportation Shipping Requirements in dollars

FTR = Fighter Sorties

BMR = Bomber Sorties

TNK = Tanker Sorties

CGO = Cargo Sorties

TSP = Transport Sorties

HEL = Helicopter Sorties

OTH = Other Flying Sorties

The final AS model was constructed similar to the previous two models except only a single independent variable, AAS, was used to forecast the dependent variable, TSP. This model is shown as:

$$TSR = \beta_0 + \beta_1 AAS + \varepsilon \tag{6}$$

where: TSR = Transportation Shipping Requirements in dollars

AAS = All Aircraft Sorties

Manpower Models. Only two types of models using the manpower variable as the only predictor variable were developed. The first model used manpower disaggregated by officer, enlisted and civilian to forecast the dependent variable TMO budget. This model is shown as:

$$TSR = \beta_0 + \beta_1 ML_1 + \beta_2 ML_2 + \beta_3 ML_3 + \varepsilon \tag{7}$$

where: TSR = Transportation Shipping Requirements in dollars

ML_1 = Officer Manpower Levels

ML_2 = Enlisted Manpower Levels

ML_3 = Civilian Manpower Levels

The second model was developed by aggregating the officer, enlisted and civilian variables into a single variable called total personnel (TP). This new variable, TP, was then used as a single independent variable to forecast the dependent variable. This model is shown as:

$$TSR = \beta_0 + \beta_1 TP + \varepsilon \tag{7}$$

where: TSR = Transportation Shipping Requirements in dollars

TP = Total Personnel Manpower Levels

Combined Models. In an effort to increase the accuracy and reliability of the regression models described, several of these models were combined. Specifically, the ML variables, both aggregated and disaggregated, were added to the AFH and AS regression equations. For each of the models discussed, a Durbin-Watson d-statistic was calculated.

Summary

This chapter presented the steps to be used in conducting this research. This research began with the selection of independent variables anticipated to be accurate predictors of the dependent variable, dollars spent shipping cargo at base level. The specific data collected included dollars spent at base cargo shipping activities, flying hours by aircraft type, number of aircraft sorties flown by aircraft type, and manpower assigned to each base in ACC. Once the data were collected, linear regression models were described which would be used to estimate the budgets for future years. These model were then evaluated using the appropriate statistical tests.

IV. Results and Analysis

Overview

The purpose of this chapter is to present the results of applying the methodology to the data collected as described in the previous chapter. The results obtained from several multiple regression models will be reviewed and discussed followed by an analysis of each model. Analysis of each model will be made for each of the three independent variables: AFH, AS, and ML.

Flying Hour Models

The first multiple regression models were developed using AFH as the independent variable to forecast the dependent variable, base level TSR. Each of the flying hour models were developed using various levels of aggregated data.

Flying Hours Disaggregated by Aircraft Type. Initially, all aircraft assigned to ACC were disaggregated and included into a single model using flying hours. The five years of budget data and flying hour data obtained from ACC resulted in 34 variables representing aircraft flying hours. The AFH variables considered in the first model include the following types of airframes:

A-10, B-1, B-2, B-52, C-130, C-135, C-21, C-27, CT-43,
E-3, E-4, E-9, EC-130, EC-135, EF-111, F-111, F-117, F-15,
F-15E, F-16, F-4, HC-130, HH-3, HH-60, KC-10, KC-135,
OC-135, OV-10, RC-135, T-37, T-38, TC-135, UH-1, WC-135.

This initial regression model included each of the flying hours for the 34 aircraft as independent variables. This model was not full rank as five variables were determined to be a linear combination of other independent variables. These five variables were subsequently removed from the model resulting in a full rank regression model consisting of 29 independent variables. Those aircraft removed from the model included the E-3,

E-9, RC-135, TC-135, WC-135 type aircraft. This revised regression model presented results which indicated that multicollinearity may be present among the independent variables. The model was significant at the 0.10 level, however, the resulting R^2 was 0.4128 with an adjusted R^2 of 0.2101. Of more significance, however only two of the 29 variables were significant at a 0.10 level. Table 4-1 shows the results from the full flying hour model disaggregated by aircraft type.

Table 4-1. Full Regression Model Results - Flying Hours Disaggregated

Aircraft Variable	Variable Estimate	Standard Error	T for Ho: Parameter=0	Probability greater |T|
A-10 Hours	2.89	2.48	1.165	0.2473
B-1 Hours	3.61	7.60	0.476	0.6355
B-2 Hours	14.25	152.98	0.093	0.9260
B-52 Hours	14.36	5.95	2.411	0.0181 *
C-130 Hours	5.54	8.31	0.667	0.5068
C-135 Hours	1621.99	2074.16	0.782	0.4364
C-21 Hours	207.80	207.99	0.999	0.3206
C-27 Hours	-155.35	395.57	-0.393	0.6955
CT-43 Hours	903.40	3161.72	0.286	0.7758
E-4 Hours	-1030.38	1157.54	-0.890	0.3759
EC-130 Hours	-3.82	15.11	-0.253	0.8010
EC-135 Hours	46.96	57.07	0.823	0.4129
EF-111 Hours	2.59	10.64	0.243	0.8083
F-111 Hours	-0.48	3.14	-0.154	0.8783
F-117 Hours	-9.09	10.60	-0.858	0.3931
F-15 Hours	0.30	3.06	0.097	0.9233
F-15E Hours	1.03	6.49	0.158	0.8746
F-16 Hours	1.74	1.80	0.961	0.3394
F-4 Hours	2.40	2.80	0.858	0.3934
HC-130 Hours	-1007.52	1007.63	-1.000	0.3202
HH-3 Hours	1251.25	1196.82	1.045	0.2988
HH-60 Hours	353.83	57.84	6.117	0.0001 *
KC-10 Hours	1.42	10.65	0.133	0.8944
KC-135 Hours	-17.04	12.92	-1.318	0.1909
OC-135 Hours	2612.66	3214.01	0.813	0.4186
OV-10 Hours	0.55	6.22	0.089	0.9297
T-37 Hours	8.38	18089	0.444	0.6584
T-38 Hours	1.42	3.93	0.360	0.7195
UH-1 Hours	-38.33	59.47	-0.645	0.5210
*** Significant at the 0.05 level**				

The number of observations included in this model was 114. The negative signs for eight of the parameter estimates, however, could not be explained as it was expected that all parameter estimates would have a positive sign.

Flying Hours Disaggregated by Categories. As described in the previous chapter several like aircraft types were placed into seven different aircraft categories, FTR, BMR, TNK, CGO, TSP, HEL, OTH, and placed into a regression model as independent variables to forecast the dependent variable. The categorized flying hour model resulted in an F-value of 3.156 which was significant at the 0.10 level. The resulting R^2, however was lower than the disaggregated model at 0.2164 with the adjusted R^2 of 0.1478. Despite a lower R^2, three of the seven variables were significant at the 0.10 level of significance. Table 4-2 shows the results from this model aggregated by aircraft categories.

Table 4-2. Regression Model Results - Flying Hours Aggregated by Category

Category Variable	Variable Estimate	Standard Error	T for Ho: Parameter=0	Probability greater |T|
Fighter Hours	2.92	1.35	2.156	0.0341 *
Bomber Hours	13.30	5.28	2.517	0.0138 *
Tanker Hours	-0.16	5.08	-0.031	0.9751
Cargo Hours	7.00	8.54	0.819	0.4152
Transport Hours	-10.83	13.57	-0.798	0.4273
Helicopter Hours	4.01	4.40	0.911	0.3649
Other Aircraft Hours	111.15	31.82	3.493	0.0008 *
*** Significant at the 0.05 level**				

The number of observations included in this model was 88. As with the previous derivative of this model, the negative signs for two of the seven parameter estimates could not be explained as again, it was expected that all parameter estimates would have a positive sign. As with the previous model, sign of multicollinearity existed with significant F-value and t-tests proving insignificant.

Aggregated Flying Hours. The last derivation of this model was accomplished by summing up the hours of all aircraft types into a single flying hour variable, AAFH. Though this has the effect of holding flying hours equal for all aircraft types, which is highly unrealistic, this was done in an attempt to determine if a better model could be developed utilizing a single variable. The results from this proved to be worse than the previous two model derivatives. The model was insignificant at the 0.10 level with an R^2 of 0.0203 and an adjusted R^2 of 0.0115.

Individual Aircraft. A final attempt to use flying hours as an independent variable to forecast base level TSR was accomplished by developing a model for each aircraft type. This was accomplished by dropping all cases in which there were zero hours flown of that aircraft type. Of the 34 models, no model was found to be significant at the 0.10 level.

Aircraft Sortie Models

A second set of multiple regression models was developed in a similar fashion as the AFH models, however the second set of models utilized AS as the independent variable to forecast the dependent variable, base level TSR. Each of the aircraft sortie models were developed using various levels of aggregated data. Each of these sortie models was developed in much the same manner as the AFH models.

Aircraft Sorties Disaggregated by Aircraft Type. As with the AFH model disaggregated by aircraft type, all aircraft assigned to ACC were disaggregated and included into a single model using AS as the independent variables. The five years of budget data and flying hour data obtained from ACC again resulted in 34 AS variables. The AS considered in this model were the same as listed in the AFH model disaggregated by aircraft type.

This model was not full rank as five variables were determined to be a linear combination of other independent variables. These five variables, which represented the

same type of aircraft removed in the AFH model, were removed from the model resulting in a full rank regression model with 29 independent variables. This revised regression model presented results which indicated that multicollinearity may be present among the independent variables. The resulting F-value was 1.8454 was significant at a 0.10 level with an R^2 of 0.3902 and an adjusted R^2 of 0.1797. Only one of the 29 variables proved to be significant at a 0.10 level. Table 4-3 shows the results from this AS model.

Table 4-3. Full Regression Model Results - Aircraft Sorties Disaggregated

Aircraft Variable	Variable Estimate	Standard Error	T for Ho: Parameter=0	Probability greater |T|
A-10 Sorties	4.48	4.44	1.011	0.3149
B-1 Sorties	30.73	43.77	0.702	0.4845
B-2 Sorties	-332.27	809.19	-0.411	0.6824
B-52 Sorties	89.25	53.91	1.656	0.1015
C-130 Sorties	-1.90	23.46	-0.081	0.9356
C-135 Sorties	747.95	2663.79	0.281	0.7796
C-21 Sorties	472.98	430.35	1.099	0.2749
C-27 Sorties	2607.50	6957.24	0.375	0.7088
CT-43 Sorties	-32613.00	84333.20	-0.387	0.6999
E-4 Sorties	-2230.33	2655.37	-0.840	0.4033
EC-130 Sorties	-30.70	75.40	-0.407	0.6849
EC-135 Sorties	322.34	403.38	0.799	0.4265
EF-111 Sorties	1.40	25.75	0.054	0.9568
F-111 Sorties	-3.19	7.09	-0.449	0.6543
F-117 Sorties	-17.85	18.56	-0.962	0.3390
F-15 Sorties	-1.20	4.58	-0.262	0.7938
F-15E Sorties	2.47	11.18	0.221	0.8255
F-16 Sorties	0.83	2.45	0.338	0.7366
F-4 Sorties	2.12	3.87	0.549	0.5843
HC-130 Sorties	-1821.80	1632.02	-1.116	0.2675
HH-3 Sorties	761.62	650.37	1.171	0.2449
HH-60 Sorties	667.18	112.75	5.918	0.0001 *
KC-10 Sorties	-5.198	47.38	-0.110	0.9129
KC-135 Sorties	-108.28	73.80	-1.467	0.1461
OC-135 Sorties	-2065.95	4950.30	-0.417	0.6775
OV-10 Sorties	2.50	11.60	0.215	0.8300
T-37 Sorties	2.94	29.35	0.100	0.9204
T-38 Sorties	1.32	4.04	0.327	0.7446
UH-1 Sorties	-98.84	94.41	-1.047	0.2981

*** Significant at the 0.05 level**

The number of observations included in this model was 114. The negative sign for 13 of the parameter estimates could not be explained as it was expected that all parameter estimates would have a positive sign.

Aircraft Sorties Disaggregated by Categories. As described in the previous chapter several like aircraft types were placed into the seven different aircraft category types and placed into a regression model as independent variables to forecast TSR. The categorized aircraft sortie model resulted in an F-value of 2.321 which was significant with an R^2 of 0.1688, which was lower than the disaggregated model. The adjusted R^2 was 0.0961. Despite a lower R^2, three of the seven variables were significant at the 0.10 level of significance. Table 4-4 shows the results from this model.

Table 4-4. Regression Model Results - Aircraft Sorties Aggregated by Category

Category Variable	Variable Estimate	Standard Error	T for Ho: Parameter=0	Probability greater |T|
Fighter Sorties	3.32	1.75	1.893	0.0620 *
Bomber Sorties	68.78	31.65	2.173	0.0327 **
Tanker Sorties	-5.51	23.28	-0.237	0.8136
Cargo Sorties	-11.48	20.72	-0.554	0.5813
Transport Sorties	-24.61	27.13	-0.907	0.3671
Helicopter Sorties	20.70	29.04	0.713	0.4780
Other Aircraft Sorties	131.70	52.81	2.493	0.0147 **

*** Significant at the 0.1 level**
**** Significant at the 0.05 level**

The number of observations included in this model was 88. As with the previous derivative of this model, the negative sign for three of the seven parameter estimates could not be explained as again, it was expected that all parameter estimates would have a positive sign. As with previous models, signs of multicollinearity existed with significant F-value and insignificant t-values.

Aggregated Aircraft Sorties. The last derivation of this model was accomplished by summing up the sorties of all aircraft types into a aircraft sortie variable, AAS. This had the effect of summing up the flying hours as done in earlier models and was accomplished for the same reasons of attempting to determine if a better model could be developed utilizing a single variable. The results from this, as in the AFH model, proved to be worse than the previous two sortie model derivatives because the F-value was insignificant. In addition, the resulting R^2 was 0.0147 with an adjusted R^2 of 0.0059.

Individual Aircraft. A final attempt to use AS as an independent variable to forecast base level TSR was made by developing a model for each aircraft type. For each aircraft type, all cases in which there were zero sorties flown were dropped. In each of the 34 models, no model was found to be significant at the 0.10 level.

Manpower Models

Two separate models were developed using ML as the independent variable to forecast the dependent variable, base level TSR. The first model was developed using disaggregated base level manpower levels, while the second model was developed using aggregated manpower levels.

Disaggregated Manpower. The first model disaggregated the ML variable into three different categories: officer, enlisted, and civilian. Manpower levels for each category were summed and placed in a regression equation to forecast base level TSR. The resulting F-value was significant at the 0.10 level with an R^2 of 0.2542 and an adjusted R^2 of 0.2276. This model included 88 observations. The results are summarized in Table 4-5.

Table 4-5. Regression Model Results - Disaggregated Manpower

Category Variable	Variable Estimate	Standard Error	T for Ho: Parameter=0	Probability greater |T|
Officer Manpower	71.37	16.64	4.289	0.0001 **
Enlisted Manpower	-192.89	74.76	2.580	0.0116 **
Civilian Manpower	126.64	66.65	1.900	0.0609 *
* Significant at the 0.1 level ** Significant at the 0.05 level				

Aggregated Manpower. The second manpower model was developed by aggregating the three independent variables, used in the prior model, into a single manpower variable, ML. As with earlier models presented, this aggregation of independent variables was accomplished in an attempt to both improve the model and reduce the number of independent variables considered in the model. The single variable model resulted in a model with an F-value significant at the 0.10 level with an R^2 of 0.1702 and an adjusted R^2 of 0.1605. This aggregated model included 88 observations.

Combined Models

In an effort to improve upon each of these models presented, the ML variable, both aggregated and disaggregated, was added to the AFH and AS models. The impact of adding the manpower variable to each of the six aircraft models listed above resulted in minimal improvement on the R^2 values.

In an effort to determine if the errors were independent, a Durbin-Watson d-statistic was computed for each of the models listed above. For each of the models, AFH, AS, and ML, the resulting d-statistic seemed to indicate that autocorrelation amongst the error terms was not present for any of the models.

Summary

This chapter presented the results of applying the methodology described in the previous chapter to the data obtained from ACC. The results from three basic types of

model were described for both the AFH and AS: disaggregated by aircraft type, disaggregated by category, and aggregated. Models utilizing ML as an independent variable was discussed as well as the results from incorporating ML into each of the AFH and AS models.

V. Conclusions and Recommendations

Overview

The primary purpose of this chapter is to draw conclusions from the results and analysis presented in the previous chapter. The objectives of this research, as identified in chapter one, will be addressed followed by a summary of the limitations to this study as well as recommendations to improve this research and recommendations for future research.

Flying Hours Models

Each of the three models developed using AFH as the independent variable for forecasting TSR proved to be unusable. In each of the three models, the resulting R^2 values were too low to make the model useful for forecasting TSR. This result was surprising as it was expected that flying hours would contribute significantly to forecasting base level TSR, since it was found that aggregated flying hours significantly contributed to forecasting SDT as reported by both Strom and Moore (Strom, 1989:85-87; Moore, 1990:150-156).

The resulting R^2 values for the first AFH model would seem to indicate that the model using AFH, disaggregated by aircraft type, was not a suitable model for forecasting base level TSR. In addition, only two of the 29 independent variables proved to be significant at a 0.10 level. Though the F-value was significant at the 0.10 level, the resulting t-values and relatively low adjusted R^2 of 0.2101 seem to indicate that AFH, disaggregated by aircraft type, cannot be used to forecast base TSR.

Despite having a greater number of significant independent variables and an F-value that was significant at the 0.10, the flying hours by categories regression model resulted in a lower adjusted R^2 value of 0.1478. This also seemed to indicate that flying

hours aggregated into aircraft categories also cannot be used to forecast TSR at base level. The results of AAFH model were similar to that of the models using AFH by category and also seemed to indicate that AAFH also cannot be used to forecast base level TSR.

Each of the models which used AFH as the sole independent variable resulted in models which could not be used reliably to forecast TSR. This result is surprising primarily because AFH was found to be a significant contributor in forecasting SDT requirements, as reported by Strom and Moore (Strom, 1989:85-87; Moore, 1990:150-156).

Aircraft Sorties Models

As with each of the AFH models, the three models developed using AS as the independent variable for forecasting TSR were unusable. In each of the three models using AS as the independent variable, the resulting R^2 values were too low, indicating that the models were not useful for forecasting TSR. Considering the results of the AFH models, his result was not surprising as the two variables are highly related.

The resulting R^2 values for the first AS model, similar to the AFH model, would seem to indicate that the model using AS, disaggregated by aircraft type, was not a suitable model for forecasting base level TSR. This model resulted in even fewer independent variables being significant at a 0.10 level, despite having an F-value which was significant at the 0.10 level.

The second AS model, which used AS by categories as the independent variable, also resulted in a model which was not usable for forecasting TSR. This model, similar to the AFH model, resulted in a greater number of significant independent variables and an F-value that was significant at the 0.10, however, it resulted in a lower adjusted R^2 value of 0.0961. This seems to indicate that aircraft sorties aggregated into aircraft categories

also cannot be used to forecast TSR at base level. The results of AAS model were similar to that of the AAFH model seemed to indicate that AAS cannot be used to forecast base level TSR.

Manpower Models

Despite a relatively low adjusted R^2 of 0.2276, the manpower model, disaggregated by officer, enlisted and civilian categories, proved to be the best model for forecasting the dependent variable base level transportation shipping requirements in dollars. The model was significant at the 0.10 level. Also, each of the three variables proved to be significant at a 0.10 level. The problem with this model, as with all of the previously discussed models, lies in its relatively low R^2 value. Though the model and each of the variables were significant, only 22 percent of the change in TMO budgets was explained by changes in officer, enlisted and civilian personnel levels. This relatively low R^2 value led to a conclusion that this model is also not an effective model to use when forecasting base level TSR. A model which aggregated these manpower variables into a single variable model only led to a lower R^2 and the same conclusions.

Recommendations

The first objective of determining if there was a relationship between AFH, AS, and ML with TSR was achieved. As mentioned earlier, a strong relationship between the independent variables, AFH, AS and ML, and the dependent variable, TSR, was not found. Though it did not result in a good model, the strongest model in this research project was realized using ML to predict TSR.

Because of the inability to effectively describe the relationship between AFH, AS, and ML with TSR, the effort to meet the second objective of developing a model that would accurately forecast TSR for future years for use in developing transportation shipping requests was not met. The results of this research led to the conclusion that

TMOs within ACC cannot use AFH, AS, or ML to accurately forecast their budget requirements for future years. It is suggested that TMOs within ACC continue to use their present naive forecasting approach, "last year plus 10%," for developing future years budgets as this type of forecasting model may be the most effective model for ensuring adequate funding until a more effective model can be developed.

Limitations

As with any research project, this project was not without limiting factors. There were several limiting factors which affected how this study was conducted and which affected the data collected. As alluded to in earlier chapters, the single largest limitation of this study was lack of finance data. Finance data was only obtainable for the previous five fiscal years. This resulted in a much smaller n than would have been desirable for this research project. It is recommended that ACC/LGT ensure that finance data for all bases in ACC is collected and maintained on an annual basis to ensure that adequate finance data is available for future research projects.

The merger of SAC and TAC into ACC in 1992 caused several problems with the loss of data. When the merger was accomplished, data from SAC was not retained by HQ ACC/FM. This made analysis of previous SAC bases impossible. This same problem was noted with obtaining flying hour data. This problem was made worse by the effects of base closure and base realignments over the past few years. Several wings within ACC had changed the aircraft mix at their airfields, making comparisons across wings much more difficult.

The loss of the LOGAIR system to move high priority cargo in 1993 may have skewed any of the regression results. The costs associated with shipping cargo in the LOGAIR system were not tracked, therefore prior to 1993 much of the cargo was moved

without direct cost to base level TMOs. Therefore the finance data used in the models did not capture the costs of moving cargo via LOGAIR

The final limitation identified while doing this research project involved not being able to quantify base location and include base location in the regression models. It is the belief of this author that that base location significantly affects the costs associated with shipping cargo at base Traffic Management Offices.

Future Research

Any future research in developing a model for forecasting TSR should focus on ensuring that more than five years of data can be obtained. Had 15 to 20 years of finance, flying hour, and manpower data been available, this research project might have successfully developed a model for forecasting TSR.

As alluded to earlier, if base location could be captured quantifiably into a regression equation, the model results would no doubt be improved. In the end, the most positive model could be developed when the Air Force achieves some sort of stability in the location and number of aircraft assigned to various wings throughout ACC.

Conclusions

The primary conclusion reached in this research project was that the current naive approach to forecasting TSR should continue to be the model used by base TMOs in forecasting their future year TSR until a more accurate and reliable model can be developed. It was further recommended that inclusion of a base location variable in a regression model might possibly be used in future research efforts.

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Vita

Captain Luke E. Closson III is from Valdosta, Georgia. He graduated from Valdosta State College in 1988 with a Bachelor of Arts degree in Speech Communication. After receiving his commission into the United States Air Force through the Reserve Officers Training Corps, and completing the Transportation Officers Course at Sheppard AFB, Texas, Captain Closson was assigned to the 27 Fighter Wing (FW) at Cannon AFB, New Mexico in 1990.

During his tour at Cannon AFB, Captain Closson served as the Flight Commander for the Combat Readiness and Resources Flight and the Flight Commander for the Vehicle Maintenance Flight.

In 1993, he was assigned to Columbus AFB, Mississippi, where he served for one year as the Chief of Transportation and Installation Mobility Officer. After completing Squadron Officer School in residence in 1994, Captain Closson entered the Air Force Institute of Technology at Wright-Patterson AFB, Ohio, and graduated in 1995 with a Masters degree in Transportation Management. He was subsequently assigned to Headquarters 8th Air Force at Barksdale AFB, Louisiana as the Chief of Transportation for 8th Air Force

Permanent Address: 604 Gornto Road
Valdosta, GA 31602

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13. ABSTRACT *(Maximum 200 words)*

This research represents an attempt to develop a quantitative tool that could be used to forecast Traffic Management Office (TMO) budget requirements for freight movements at base level within Air Combat Command. Regression analysis, using aircraft flying hours, aircraft sorties, and wing manpower levels as independent variables to predict shipping costs, was used in this research project. Each of the independent variables was aggregated and disaggregated at various levels in an attempt to develop a simple but accurate model. The results seem to suggest that aircraft flying hours, aircraft sorties, and wing manpower levels are not accurate predictors of TMO freight shipping requirements. Of the three independent variables, the most useful variable for forecasting TMO freight shipping requirements was the manpower variable, not aircraft flying hours or aircraft sorties as expected. Because of these results, the author recommends the continued use of the current naive forecasting method until a better model is developed.

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